Multi-Period Optimization of Energy Demand Control for Electric Vehicles in Unbalanced Electrical Power Systems Considering the Center Load Distance of Charging Station Areas

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Abstract. *The rise of plug-in electric vehicles (EVs) impacts the energy demand of power systems. This study employed a multi-period power flow analysis on the IEEE 123 node test system, which was optimized for the installation of 6-position EV charging stations. Temporal load shifting was utilized to control the charging intervals of electric vehicles. Non-dominated Sorting Genetic Algorithm (NSGA-II) was applied to determine the optimal locations for installing EV charging stations, considering target functions, such as total energy loss, voltage unbalance factor (VUF), and center load distance. The results showed that the center load distance resulted in the optimal charging station location in the central area of the system, different from conventional considerations. The results showed that installing the charging station in the center of the load group (case 4) increased the total energy loss and VUF compared to installing it at the root of the load group (case 3) by about 2.1134 and 1.2287%, respectively. However, EVs reduced impacts during periods of system weakness. By controlling charging intervals during off-peak times (case 6), total energy loss and VUF were decreased by 4.7070 and 5.6896%, respectively, which effectively reduced energy demand during peak periods.*

Keywords:
center load distance, energy demand, EV charging station, multi-period power flow, NSGA-II, temporal load shifting, voltage unbalance factor

1. Introduction

A. Significance and Problem

Nowadays, there are notable variations in the load required by power users, which has led to a sharp rise in energy demand. The energy-consuming sectors include transportation, industrial, and household sectors. Enhanced and contemporary technical advancements are significant departures from the past, which mainly relied on fossil fuels including coal, oil, and natural gas. However, these fossil fuels adversely affect the environment. Therefore, energy management and the utilization of renewable energy in various forms to support load expansion in order to appropriately accommodate load changes are crucial and essential [1]. This is particularly true for the expansion of the load of electric consumers in the distribution system, particularly the load of electric vehicles as a contemporary load [2]. Electric vehicle loads are contemporary loads for which energy consumption prediction is challenging. Thus, complex user behavior and charging patterns, appropriate charging station placement in electrical systems, and appropriate administration are essential [3, 4].

B. Overview of EVs in the power system

Electric vehicles (EVs) have gained significant attention in recent years due to their potential to revolutionize the transportation sector and contribute to a more sustainable and environmentally friendly future. As EV adoption continues to grow, it is essential to understand their impact on power systems. This literature review provides an overview of research conducted on the integration of EVs into power systems, focusing on their benefits, challenges, and the various strategies proposed to manage their integration effectively. The increasing adoption of EVs is crucial in transitioning towards a greener economy, effectively bridging the transportation and energy sectors. Understanding the impact of EVs on power systems is essential, especially in the context of an evolving electrical grid [5] as shown in Fig. 1.

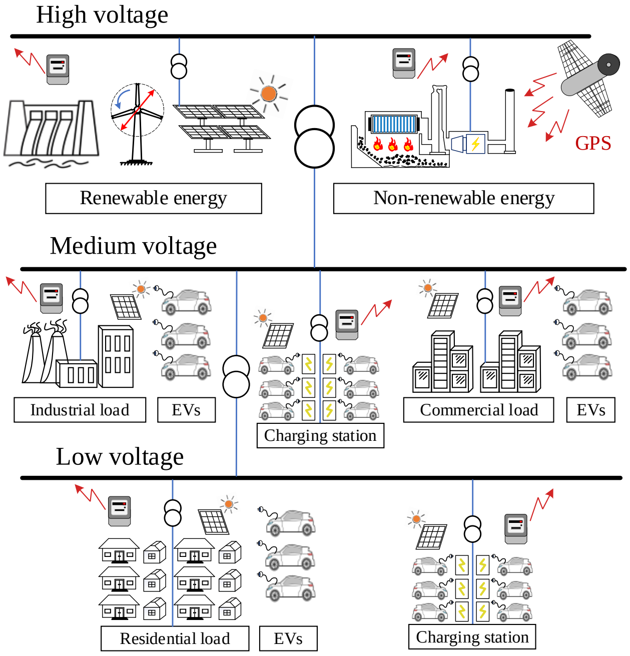

Fig. 1 Integration of electric vehicle into the grids.

A review on the integration of EVs into power systems delves into the multifaceted role of EVs within power systems, emphasizing their potential as dynamic components of the broader electrical grid [6]. Significant contributions include investigations into the role of EV parking lots (EVPLs) in supporting the electrical grid. This study demonstrates how EVPLs can actively modify their charging schedules in response to grid demands, thereby offering a flexible demand-side solution [7]. These developments underscore the potential of EVs in enhancing grid stability and efficiency, showcasing their proactive role in energy management. The benefits of EVs in power systems are manifold. They support the grid, integrate with renewable energy sources, and significantly impact emission reduction [8]. However, integrating EVs into the electrical power system faces challenges, including changing infrastructure, grid integration issues, and concerns about battery degradation. Addressing these challenges is crucial for seamless integration [9]. Ongoing research and innovations are vital for developing strategies for effective integration, such as smart charging, vehicle-to-grid (V2G) technologies, and implementing relevant policy and incentives [10, 11]. Structured into three main sections, this overview probes the multifaceted role of EVs in power systems as shown in Fig. 2. It provides a detailed analysis of the current state of EV integration, explaining the innovative solutions and strategies proposed to harmonize the relationship between EVs and the electrical grid, ultimately contributing to a more sustainable and efficient future.

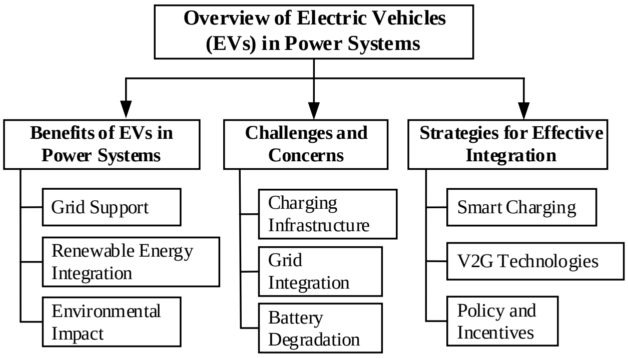

Fig. 2 Overview of EVs in the power system.

C. Literature Review

In recent years, market penetration of EVs has increased substantially due to the accelerated development of EV-related technologies; this has caused charging stations to experience a greater demand for charging capacity. The electric vehicle chargers are equipped to consume energy from the grid enabling the electric vehicle to operate. Determining the appropriate position of the charger for electric vehicles in relation to the driver's usage behavior must be considered in order to minimize the energy use of the electrical system. Past research has presented principles for determining the appropriate location, many of which focus on reducing and mitigating problems with the electrical system [12-14]. The best location for fast charging stations (FCSs) is determined by using a mixed-integer linear programming (MILP) model, examining how plug-in electric vehicle (PEV) owners react to changes in electricity prices, and an improved flow-capturing location model in an urban network. The distribution company (DISCO) is obligated to offer electricity to individuals at exorbitant rates, resulting in customer attrition. Thus, investing in stations that supply consumers with electricity at a reasonable cost will encourage PEV owners to utilize their vehicles more frequently, resulting in increased revenue and a short payback period. Meanwhile, integrating the wind energy into the grid can cause uncertainty and make it difficult to maintain optimal conditions [15]. The high penetration level of EVs is causing new issues in future power systems due to the high charging load. Therefore, charging demand estimates, drivers' preferences and the cost of charging stations were adapted and formulated to minimize the non-convex problem of peak charging demand using integer nonlinear programming. The optimal charging control was limited to peak demand control and did not consider the impact of grid losses [16]. The optimal allocation of plug-in EV charging stations (PEVCSs) was integrated with the radial distribution systems. The impact of the PEVCSs could be moderated by photovoltaic (PV) systems. However, PV systems were defined by using static state power injection and were not related to solar irradiance in a realistic way [17]. An operational strategy to reduce the computational burden of high-percentage electric vehicle charging was proposed by using clustering techniques to group EVs with similar attributes and behaviors into different clusters. This method could reduce the complexity of charging control, the investment and operation costs. The focus was on the energy consumption, operating costs, and state of charge (SOC) of EVs, rather than grid stability factors like voltage level and total power loss [18]. The modified Archimedes optimization algorithm (MAOA) was used to determine the optimal placement of EV charging stations in distribution networks under conditions of power loss, voltage deviation, and voltage stability index (VSI). The MAOA was presented as the best solution for the objective function. The optimal location of EV charging stations was defined by clustering the group that presented the best location based on the nearest root node of the electric vehicle charging stations [19]. The critical load restoration was presented by incorporating the spatio-temporal scheduling of EVs. This approach, which used an optimization model, examined a variety of scenarios with different recovery strategies, confidence levels in chance constraints, and penalty factors. The effectiveness of this strategy is convincingly demonstrated and validated within the study [20]. The reviewed literature employs various methodologies, such as centralized control strategies, PV generation forecasting, and coordinated control of devices like distribution static synchronous compensator (DSTATCOM) and on-load tap changers (OLTC). Their contributions include improved voltage regulation, reduced power losses, and enhanced coordination in power distribution systems with increased renewable energy integration. The discussion underscores challenges in local control methods, the trade-off between accuracy and computational efficiency, and the necessity of accounting for uncertainties in renewable energy penetration. These findings advance the development of effective control strategies for contemporary power distribution networks [21]. A novel optimization scheme of the electrical power system was proposed for active distribution systems. It achieved a 75% reduction in computational time compared to conventional methods. The scheme integrated voltage and var optimization (VVO), demand response (DR), and network reconfiguration (NR) strategies, addressing the limitations of independent handling. Tested on the IEEE 123-node test feeder with EV and PV penetrations, it significantly reduced peak demand and energy loss, improving overall EDN efficiency and reliability. The modular approach lowered the computational burden and yielded high-quality solutions, while the optimal topology demonstrated substantially reduced loss and unbalance factors, showcasing its practical potential [22]. A smart grid management approach employed a vital algorithm for EV charging in unbalanced low-voltage distribution systems, showing effective real-time performance. This algorithm significantly reduced unbalanced distribution total power consumption (UDTPC) in various scenarios involving EVs. The most impactful results were achieved with complete EV integration, thereby improving power efficiency. However, it should be noted that phase balancing in the EV charging process could not effectively reduce grid voltage unbalance, indicating an area for potential improvement in the system's design or operation [23]. A data-driven distributional robust optimization framework to address uncertainties in distribution network operation was presented by focusing on EV fleets and PV generation. The key contribution was the introduction of this innovative framework, which was applied to IEEE 34-bus and IEEE 123-bus networks. This uniquely offered a practical solution to handle uncertainties and improve network performance. The discussion emphasized the advantages of this approach over traditional methods like stochastic programming and robust optimization, particularly in terms of enhancing EV availability and access to charging stations, ultimately contributing to more efficient and resilient network operation [24].

D. Summary of Major Contributions

This study proposed the use of the concept of center node of group for finding the optimal electric vehicle charging station in a distribution network. Research gap of this paper is presented by the existing methods from the previous literature reviews as shown in Table 1. The optimization problem was formulated as a multi-objective minimization problem and solutions performed from case studies. The key contributions of this article are presented as follows:

1) A novel framework based on the center node of a group for electric vehicle charging stations under center load distance techniques was proposed.
2) This framework was different from previous frameworks presented in literature, which focused on root node of group for installing electric vehicles charging station.
3) The novel framework of centroid node of EVs charging zone was used to control bus voltages, address voltage unbalance, energy loss and energy control demand. This approach represents the first attempt to the best of our knowledge.
4) Multi-period was adapted to solve the optimal problem and investigate the impact of EVs charging stations on the distribution network.

Table 1 Comparison with existing methods

Ref.	PM	OB	CM	MP	SP	UF	EL	VI	TL	VS	PS	FG	RG	CG
[15]	BP	SO	-	✓	-	-	-	-	✓	-	-	-	✓	-
[16]	-	SO	DC	✓	-	-	-	-	✓	-	✓	-	-	✓
[17]	BP	MO	-	-	✓	-	-	-	✓	✓	-	-	✓	-
[18]	-	MO	DC	✓	-	-	-	-	-	-	-	-	✓	-
[19]	BP	MO	-	-	✓	-	-	✓	✓	✓	-	✓	-	-
[20]	BP	SO	CC	✓	-	-	-	-	✓	-	-	✓	-	-
[21]	UP	SO	CC	✓	-	✓	✓	-	-	-	-	✓	-	-
[22]	UP	MO	CC	✓	-	✓	✓	✓	-	-	-	-	✓	-
[23]	UP	SO	CC	✓	-	✓	✓	-	-	-	✓	✓	-	-
[24]	UP	SO	CC	✓	-	-	-	-	-	-	✓	✓	-	-
Proposed	UP	MO	CC	✓	✓	✓	✓	-	-	-	✓	-	-	✓

Remark:

PM = Power flow method, BP = Balanced power flow, UP = Unbalanced power flow, OB = Objective function type, SO = Single objective function, MO = Multi-objective function, CT = Control method, DC = Distributed control, CC = Centralized control, MP = Multi-period power flow, SP = Single period power flow, UF = Unbalanced voltage factor, VI =Voltage deviation index, EL = Energy loss, TL = Total power loss, VS = Voltage stability Index, PS = Peak shaving, FG = Fix point charging of group, RG = Randomize charging of group, CG = Centroid node charging of group

2. Problem Formulation

A. Conceptual Framework of Power Flow Analysis

An analysis of power flow was presented using nonlinear equation analysis method. This complex analysis can be applied using Open Distribution System Simulator (OpenDSS) [25, 26], a sophisticated computer tool developed for simulating and analyzing electrical systems. It is adept at simulating the operations of electrical energy management systems across a spectrum of power systems, from small-scale to large-scale. The OpenDSS is particularly effective in simulating the flow of electrical energy. Key features of this tool include the ability to perform voltage calculations, identify problems through detailed analysis, and test multiple scenarios in power systems by considering node current metrics. The application of Amitan and the voltage provided by the Node are demonstrated in Fig. 3 and explained in [27].

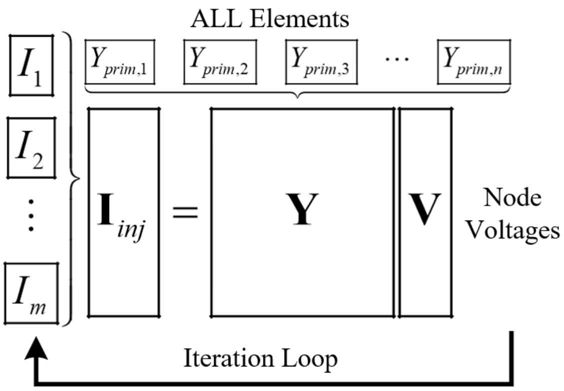

Fig. 3 Iteration of the OpenDSS solution for power flow problems based on matrices.

B. Probability of plug-in electrical vehicles load

The behavior of electric vehicles is crucial in determining the magnitude of the load they impose when plugged into the power grid. Factors such as daily start time, frequency of travel, driving distance (in kilometers), and driving duration (in minutes) influence the load of PEVs. The driving distance relates to the capacity of battery energy and is the main factor influencing the quantity of power used from the grid. The charging power per PEV is calculated based on the battery charging capacity (kW) and a power factor (pf) of 0.85, taking into account the SOC of the battery. The probability of charging can be calculated as shown in (1) [3].

$$F_A = (t, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(t-\mu)/2\sigma^2} \;;\; 0 < t < N \tag{1}$$

where: F_A is the probability of charging at a given arrival time, t is the time period, μ is the mean value, σ is the standard deviation of the normal distribution and N is number of periods.

C. Total energy loss of the electrical power system

The total power loss of a system can be determined under constant conditions for a specified period. Typically, this loss is estimated during peak times of electrical power demand. When conducting power flow analysis across multiple periods, the total power loss for each period is identified as the total system losses for that specific period [28]. This concept is mathematically expressed in (2) and (3).

$$P_{loss} = I^2 \times R \tag{2}$$

$$E_{loss} = \int_1^N P_{loss}(t)\, dt \;;\; 0 < t < N \tag{3}$$

where: P_{loss} is the real power loss of the system, I is current in the transmission line, R is resistance of transmission line, E_{loss} is the energy loss of the system, t is the time period and N is the number of periods.

D. Voltage unbalance factor

The voltage unbalance factor (VUF) is an index used to assess the variance in voltage magnitude across different phases. Inadequate design and management of a distribution system can lead to voltage variations when load power is consumed at various intervals, which may cause several issues in the electrical system. Therefore, monitoring and mitigating these voltage variations to acceptable limits is crucial for the reliable operation of the power distribution system. According to EN 61000 and IEC 61000-2-4 standards for medium voltage analysis, the Voltage Unbalance Factor should not exceed 2%. Similarly, the ANSI C84.1 standard dictates that this factor should be controlled to a maximum of 3%. The calculation of the voltage unbalance factor involves the ratio of symmetrical components in negative and positive phase sequences [29], as demonstrated in (4) and (5).

$$vuf = \frac{V_+}{V_-} \times 100 \tag{4}$$

$$VUF = \max\left[\mathrm{vuf}\left(t\right)\right]\ ;\ 0 < t < N \tag{5}$$

where: vuf, VUF is the percentage of voltage unbalance factor, V_+ is the magnitude of the negative sequence voltage, V_- is the magnitude of the positive sequence voltage, t is the time period and N is the number of periods.

E. Center Load Distance

In this research, a principle for determining the optimal location for installing new electric vehicle charging station is presented. The fundamental principle is that installing a charging station near the source area of the system minimizes system losses. Additionally, selecting an installation point at the center of the system is another important factor. To address this, we propose the 'Average Shortest Distance' method. This method calculates the average distance a motor vehicle travels from a potential location to the system's center in each zone. This average distance is then compared with the maximum distance within the zone. The details of this method are illustrated in Fig. 4 and explained in (6) - (8).

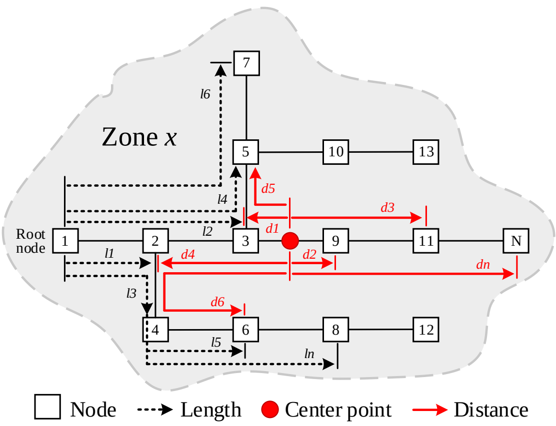

Fig. 4 An example of center load distance.

$$Center = \sum_{i}^{n} \frac{l_i}{n} \tag{6}$$

$$d_i = \left| l_i \pm Center \right| \tag{7}$$

$$Dis_i = \frac{d_i}{d_{\max}} \tag{8}$$

where: $Center$ is the center point of the zone, l is the length of node (i), d is the distance between the root node and any node (i) and Dis is the normalized value of distance function.

F. Non-Dominated Sorting Genetic Algorithm

The Non-dominated Sorting Genetic Algorithm (NSGA-II) is a modified version of the traditional Genetic Algorithm (GA) designed to address multi- objective optimization problems with multiple. The NSGA-II is a popular tool used in many research because it can provide reliable results in multi-objective optimization problems with conflicting objectives. It has efficient structure and working methodology allowing for fast processing. Therefore, NSGA-II has been widely adapted to solve complex optimization problems by many researchers in the engineering field [30-35]. The key concepts in the NSGA-II are as follows:

Fast Non-dominated Sorting: population members are sorted using the fast non-dominated sorting algorithm. The population members are sorted by using concept of Pareto dominance.

Elite preserving operator: the population members that are not dominated will be directly transferred to the next generation till some solutions dominate them.

Crowding Distance: maintain diversity of the population in generations by using the crowding distance to transfer them to the next generation.

Selection Operators: the procedure for the next generation is delivered by the population members and chosen using a crowded tournament selection mechanism. The NSGA-II processes are repeated until a maximum number of generations or satisfactory convergence is reached.

G. Best Compromise Solution

The best compromise solution (BCS) is a concept that involves solving multi-objective problems. The BCS tries to find the most satisfying answer possible by considering the challenges that arise from having to compromise between different objectives. The problem of multi-objective solution is selected in the best value from the result space. The BCS method is based on the Euclidean distance technique, which is used to select the best of Pareto result in the Cartesian coordinate system, is presented in (9) and (10) [36].

$$D = \sqrt{f_1^2 + f_2^2 + f_3^2} \tag{9}$$

$$best = \min\left(D\right) \tag{10}$$

where: D is the value of the available solution for all objectives, f_1, f_2 and f_3 are the corresponding objective functions in the feasible region.

3. Proposed strategy and methodology

This study modified the IEEE 123 node test system, which is an unbalanced load distribution system that is similar in complexity to the actual electrical system, to install six charging stations in each zone, as shown in Fig. 5.

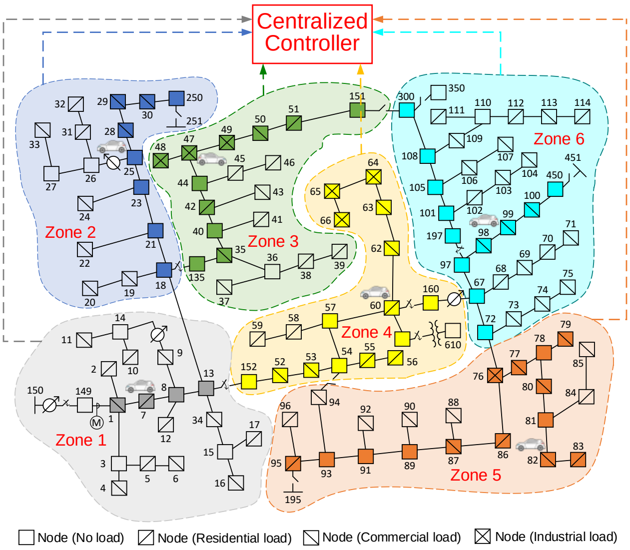

Fig. 5 Modified IEEE 123 node with integration of 6 charging stations in each zone.

A. Load profiles of the IEEE 123 node

The energy consumption of the connected loads on the grid, which fluctuates based on the consumption patterns of various electricity consumers, has an impact on time-series analysis of electrical systems. Data was typically recorded every 15 minutes, resulting in 96 periods per day. This data was categorized based on the type of electricity consumer, including small, medium, and large enterprises, specialized enterprises, or residential houses. However, to analyze power systems, the modeling of the power demand profile should be tailored to the specific nature of the study. This involves identifying seasonal load types or segmenting them according to periods of high and low demand within a day [37, 38]. In this study, we presented a profile of the electrical power needs of residential users. The power consumption patterns of businesses and industries are illustrated in Fig. 6.

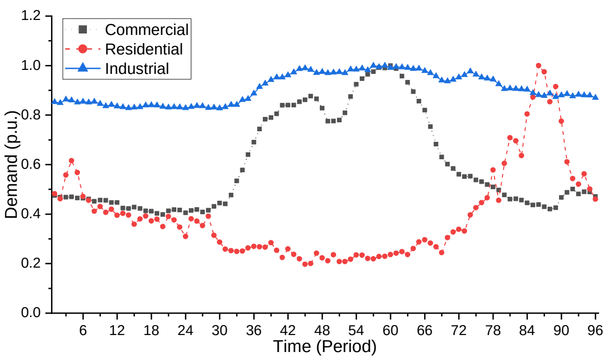

Fig. 6 Load profiles of study cases.

The complexity of the IEEE 123 node test system, which comprises nodes with both three-phase and one-phase load connections, significantly complicates the analysis of electrical system issues. To determine the VUF, denoting voltage imbalance in a three-phase system, it is necessary to select potential nodes by calculating the sequential value in the problem analysis, as illustrated in Table 2.

Table 2 Data order of three-phase for solving VUF

Order	Node	Order	Node	Order	Node
1	1	20	51	39	86
2	7	21	52	40	78
3	8	22	53	41	79
4	13	23	54	42	80
5	18	24	55	43	81
6	21	25	57	44	82
7	23	26	56	45	83
8	25	27	60	46	87
9	28	28	61	47	89
10	29	29	62	48	91
11	30	30	63	49	93
12	35	31	64	50	95
13	40	32	65	51	98
14	42	33	66	52	99
15	44	34	67	53	100
16	47	35	72	54	101
17	48	36	97	55	105
18	49	37	76	56	108
19	50	38	77	-	-

B. Objective functions

In this study, objective functions were selected by comparing three target function values to identify the minimum and most appropriate values based on the energy loss, the voltage unbalance factor and shortest distance of charging stations. These values' parameters were refined using the per unit method for a uniform comparison of various system values. The NSGA-II approach of the best compromise solution was then used to find the minimal value represented in (11) - (14).

$$\min(f) = [f_1,\ f_2,\ f_3] \tag{11}$$

$$f_1 = E_{loss} / E_{loss,base} \tag{12}$$

$$f_2 = VUF / VUF_{base} \tag{13}$$

$$f_3 = Dis_1 + Dis_2 + Dis_3 + \ldots Dis_n \tag{14}$$

where: f_1, f_2 and f_3 are the objective functions, $E_{loss,base}$ is the energy loss (Base Case) of the system, VUF_{base} is the percentage of voltage unbalance factor (Base Case) of the system and Dis is the normalized value of distance of EV station.

C. Constraints

Equality constraints: The power requirements of the grid are related to the apparatus and power system networks:

$$P_{grid} - \sum_{i=1}^{n} P_{Load}^{i} - \sum_{i=1}^{n} P_{EV}^{i} - P_{Loss} = 0 \tag{15}$$

Inequality constraints: This research focused on the node voltage constraints, power demand of EV charging stations, and state of charge (SOC) of the EVs for charging when arriving and departing, as follows:

$$\begin{cases} |V_i|_{\min} \le |V_i| \le |V_i|_{\max} \\ P_{i,\min}^{EV} \le P_i^{EV} \le P_{i,\max}^{EV} \\ SOC_{i,\min}^{EV} \le SOC_i^{EV} \le SOC_{i,\max}^{EV} \end{cases} \tag{16}$$

D. Energy demand control of EVs

This study primarily focused on the effective management of energy demand at EVCSs. The chosen approach was simulating Type 2 charging stations, which are standardized models capable of accommodating both single-phase and three-phase charging. These simulated stations were characterized by a maximum capacity of 22 kW, an input voltage of 400 V, and a maximum current of 32 A, adhering to the standards set by IEC 62196-2 and IEC 61851-22/23 [13]. To facilitate this investigation, six EV charging stations were designated for installation, each equipped with six charging slots. Within the scope of this research, careful consideration was given to the time intervals for charging electric vehicles. These intervals were determined based on driver behaviour, closely mirroring the energy consumption patterns during EV operation. They were subsequently categorized into four distinct charging periods:

08:00 AM for morning work hours.
01:00 PM for afternoon work hours.
05:00 PM for post-work hours.
10:00 PM for residential charging.

Moreover, the study implemented temporal load shifting as the key strategy for managing energy demand in EVs charging [39]. Additionally, the implementation of centralized control for EVs to effectively mitigate peak electricity demand was explored. These control strategies were executed in two modes: firstly, by averaging the charging intervals throughout the day, and secondly, by focusing on specific off-peak hours from 10:00 PM to 09:00 AM. Detailed information regarding these approaches can be found in (17).

$$EVs_{control} \begin{cases} Normal\ ;\ Time_{start,stop} \in Off\_peak \\ Shifting\ ;\ Time_{start,stop} \in On\_peak \end{cases} \tag{17}$$

E. Solution process

It is difficult to estimate EV loads regarding the number and energy required for charging process. This research attempted to manage optimal EV charging under the center load distance of the charging area. Optimal location for installing EV charging stations was demonstrated by defining the charging time center and presenting the optimal condition under center load distance. The solution process was divided into six steps as follows:

Step 1: Modifying IEEE 123 node test system to facilitate multi-period power flow analysis by incorporating residential, commercial, and industrial load profiles.

Step 2: Partitioning the load into six zones, considering potential installation locations for six electric vehicle charging stations.

Step 3: Simulating the load behavior of plug-in electric vehicles in order to ascertain the electrical energy requirements of charging stations.

Step 4: Conducting a nonlinear equation analysis of the power flow through the COM interface between OpenDSS and m-files. This analysis considered the target functions, which consisted of electrical power loss, average shortest distance, and VUF.

Step 5: Considering the optimal charging station placement by using the NSGA-II and simulate the control of the energy demand associated with EVs.

Step 6: Implementing the temporal load shifting technique to regulate the charging schedule for electric vehicles, using the mean charge duration over the course of the day and only take into account the charging during periods of low demand.

The case studies for testing the system were established by determining the location of the EVCS and installing six charging stations in six zones of the system. The NSGA-II was used for multi-period optimization of energy demand control for EVCS. The centralized control for EVs was used for managing energy demand in EVs charging. Therefore, the impact of electric vehicle charging stations on energy demand problem was illustrated through the utilization of the IEEE 123 node. Controlling the energy demand of electric vehicles within an unbalanced electrical power system was delineated by categorizing it into six distinct cases as follows:

Case 1: Base case, the IEEE 123 node was used for power flow analysis with single-period power flow conditions based on peak load demand.

Case 2: Multi-period power flow was used for power flow analysis by determining the load profile of residential, commercial, and industrial areas.

Case 3: Determined the optimal installation point for an EVs charging station by using multiple objective functions, including energy loss of the system and the maximum voltage unbalance factor, to simulate charging behavior at the EV driver's station in four time periods.

Case 4: Considered the optimum installation point for EV charging stations using the objectives of energy loss of the system, maximum voltage unbalance factor, and the normalized value of the distance from the EVs station.

Case 5: Considered installing the EVs charging station in the center of the load group and controlled the EV charge intervals averaged throughout the day.

Case 6: Considered installing the EVs charging station in the center of the load group and controlled the charging interval EV by charging only during the off-peak period.

4. RESULTS AND DISCUSSION

This study focused on mitigating the severity of electrification usage changes in power system during EV charging. The objective was to establish a foundation using real case electrical system analysis. It should be noted that charging stations cannot always be installed directly at the power source entry. This research highlighted key differences and recommendations that could be used for future application to actual electrical systems. The results of each case study are presented as follows:

A. Case 1

This case involved the power flow analysis of the IEEE 123 node test system using a single-period power flow method, based on peak load demand. The analysis identified the maximum actual power loss to be approximately 13,198 kW, which occurred in transmission line No. 3 (from node No. 1 to node No. 7). This line is in the root node area of the test system as illustrated in Fig. 7.

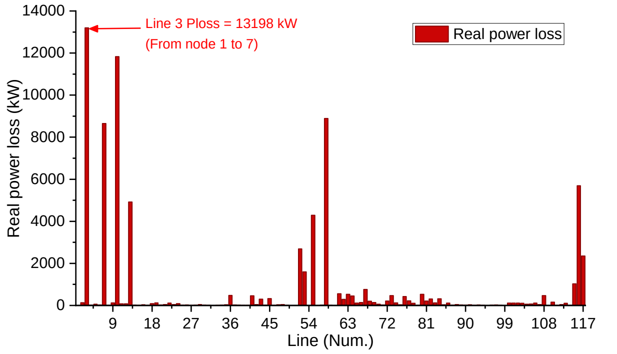

Fig. 7 Actual power loss profile in power transmission lines for Case 1.

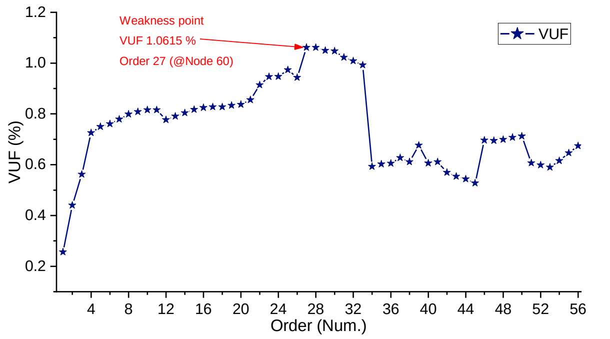

Fig. 8 VUF profiles of Case 1.

The VUF profiles of the three-phase load connections is illustrated in Fig. 8. The analysis revealed that order 27 (Node No.60), which represented the center of the test system, exhibited a maximum VUF of approximately 1.0615%. In contrast, the order 1 (Node No. 1), which represented the root node area, displayed a minimum VUF of approximately 0.2563%. Nevertheless, the mean VUF of the system was estimated to be around 0.7577%.

B. Case 2

The findings derived from the simulation of the multi-period power flow analysis indicated that the maximum overall actual power loss of around 14.2399 kW consistently occurred at period 60 (03:00 PM). Similarly, the maximal total real power loss occurred at period 24 (06:00 AM), where it remained relatively constant at approximately 4.4569 kW. The system consistently experienced a total energy loss of approximately 1,041 kWh, which provided significant insight into the actual power system loss profile as illustrated in Fig. 9.

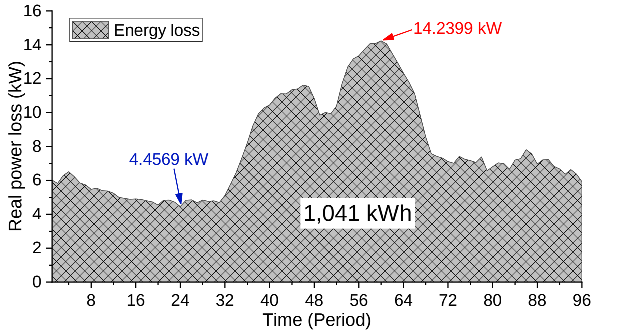

Fig. 9 Actual power loss profile in power transmission lines for Case 2.

Figure 10 illustrates the results of the VUF at the nodes connected to a transmission line in the model. The study found that the VUF value at each node varied according to the power consumption behavior of different load profiles. Notably, the maximum VUF value was observed at node number 60 during data order no. 27 (which corresponded to 3:00 PM), with an approximate value of 0.9034%. This represented the coordinates and time of the weakness point in the test system.

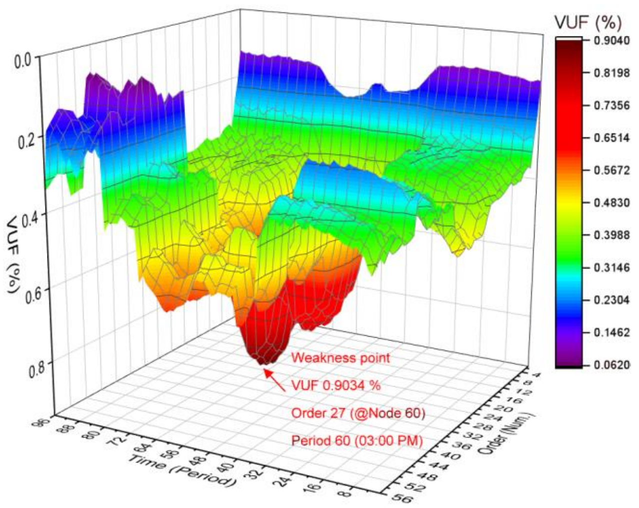

Fig. 10 VUF profiles for Case 2.

C. Case 3

Figure 11 shows the Pareto front results of the NSGA-II optimization method. The compromise solution method was used to show the optimal location for the installation of EV stations in zones 1 to 6 at nodes No. 1, 18, 35, 52, 80, and 67, respectively. The selected solution showed that the energy loss of the system was about 1.6398 p.u. The voltage unbalance factor was about 1.1002 p.u..

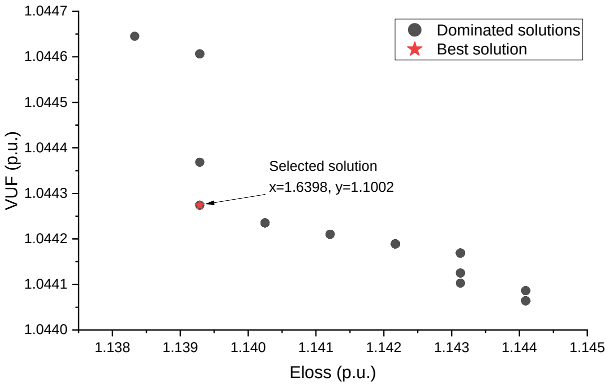

Fig. 11 A pareto front to find the optimal location of EV stations for Case 3.

The simulation results of installing the EV charging station at root node of the zone showed that the maximum total real power loss at period 55 (01:45 PM) was about 21.1478 kW. The minimum total real power loss at period 24 (06:00 AM) was about 4.4569 kW. The total energy loss of the system was about 1,186 kWh, which shown in Fig. 12.

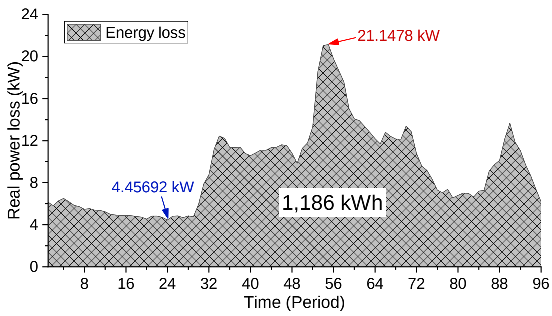

Fig. 12 Actual power loss profile in power transmission lines for Case 3.

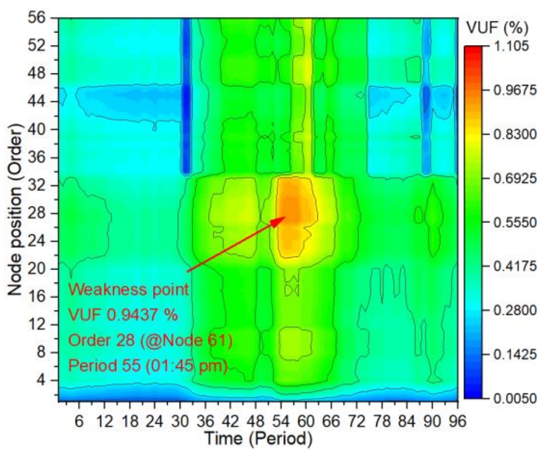

Fig. 13 VUF contour for Case 3 with installation on the root node of the grid.

Figure 13 illustrates the results of the (VUF when an electric vehicle charging station was installed at the source of the power transmission system. The maximum VUF, observed at Node No. 61 during period 55 (01:45 PM), was 0.9437%. This highlights a position and period of grid weakness that differed from Case 2.

D. Case 4

Figure 14 presents the Pareto front obtained from the equation used to identify the most suitable value via the NSGA-II algorithm. The algorithm identified the best compromise solution, which indicated the optimal locations for installing EV stations in zones 1 to 6 were at node numbers 7, 25, 47, 60, 82, and 99, respectively. The selected solution showed that the energy loss of the system was about 1.1604 per unit (p.u.). The voltage unbalance factor was approximately 1.0569 p.u., and the distance function value was around 0.6068 p.u.

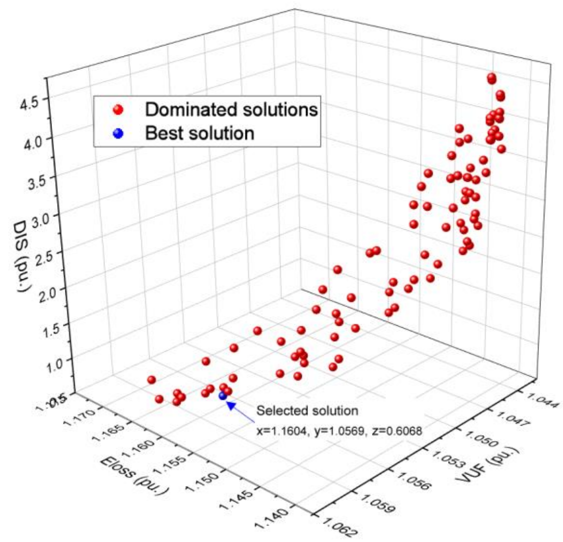

Fig. 14 A pareto front to find optimum location of EV stations for Case 4.

The simulation results of installing the EV charging station at center point of the zones showed that the maximum total real power loss at period 55 (01:45 PM) was about 21.2135 kW. The minimum total real power loss at period 24 (06:00 AM) was about 4.4569 kW. The total energy loss of the system was about 1,208 kWh. The total energy loss was higher than installing the EV charging station at root node of the zone (case 3) as shown in Fig. 15.

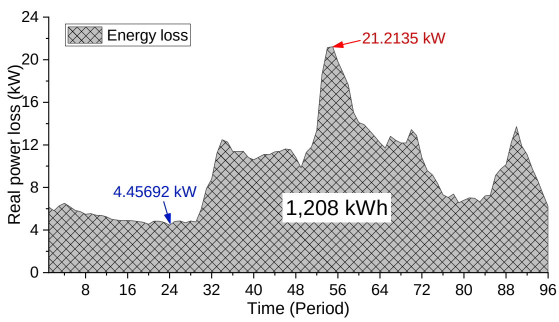

Fig. 15 Actual power loss profile in power transmission lines for Case 4.

Figure 16 displays the impact of the VUF for Case 4, where EV charging stations were installed at the center of the load group. The simulation of the clients' charging behavior was divided into 4 time periods. The test results revealed that the maximum VUF at Node No. 61 during Period 55 (01:45 PM) was 0.9548%, indicating an increase from Case 2. This increase occurred in conditions without the electric vehicle load connection and exceeded the impact observed when EV charging stations were installed at the source of the load group (zone 3).

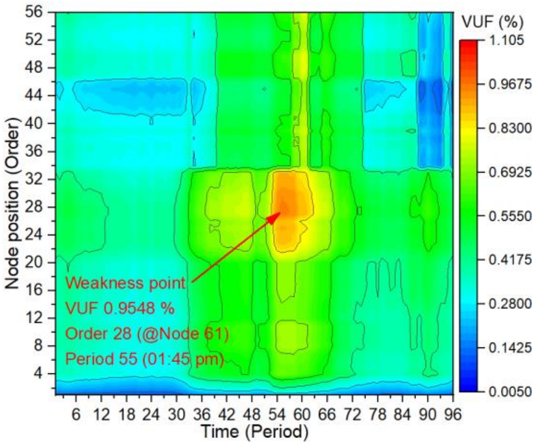

Fig. 16 VUF contour for Case 4 with EVs charging installation at the centroid node of grid zone.

E. Case 5

The simulation results obtained by installing the EV charging station at the center point of the zone (case 5) showed that the maximum total real power loss at period 55 (01:45 PM) was 15.7348 kW. The minimum total real power loss at period 24 (06:00 AM) was 5.4150 kW. The total energy loss of the system was about 1,167 kWh, which was less than that of Case 4. The charging time of the charging station was based on the average values of the daytime. The real power system loss profile is presented in Fig. 17.

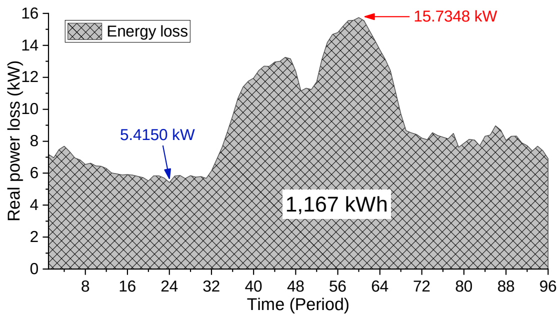

Fig. 17 Actual power loss profile in power transmission lines for Case 5.

Figure 18 displays the impact of the VUF when EVCSs were installed at the center of the load group (zone). The simulation averages the clients' charging behavior throughout the day. The test results showed that the maximum VUF at Node No. 61 during Period 60 (03:00 PM) was 0.9182%, which was lower compared to specific time periods for EV charging.

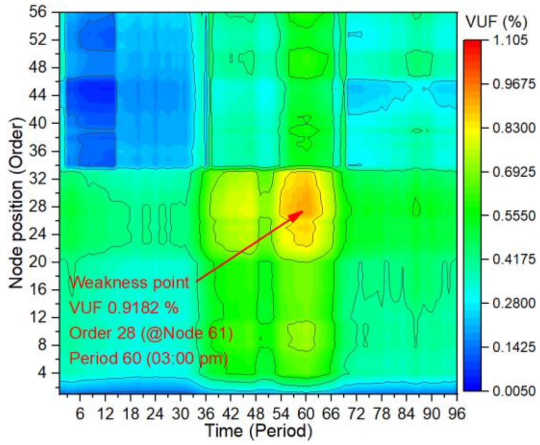

Fig. 18 VUF contour for Case 5 with EVs charging installation at the centroid node of grid zone.

F. Case 6

The simulation results of installing the EV charging station at the central point of the zone (Case 6) indicated that the maximum total real power loss at Period 60 (03:00 PM) was 14.2399 kW, while the minimum total real power loss at Period 32 (08:00 AM) was 5.2119 kW. The total energy loss of the system was 1,159 kWh, which was the lowest power loss among all case studies. The real power system loss profile is presented in Fig. 19.

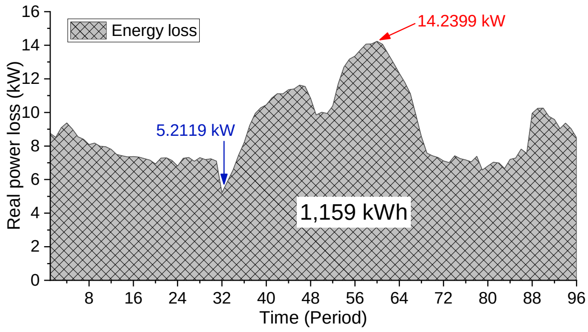

Fig. 19 Actual power loss profile in power transmission lines for Case 6.

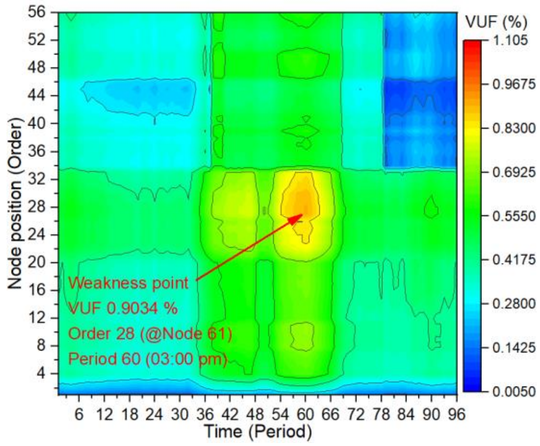

Fig. 20 VUF contour for Case 6 with EVs chargingat the centroid node of the grid zone.

Figure 20 depicts the impact of the VUF when EVCSs were installed at the center of each load group in different zones. The simulation modelled the charging behavior of drivers, with charging being evenly distributed throughout the day during off-peak periods. The test results showed that the maximum VUF at Node No. 61 during Period 60 (03:00 PM) was approximately 0.9034%. This value was lower compared to EV charging with an average daily distribution (Case 5).

G. Summary of simulation results

Table 3 Summary of simulation results of the case studies

Case Study	Eloss (kWh)	VUF,max (%)	DIS (pu.)	EVs position (Node No.)
Case 1	-	1.0615	-	-
Case 2	1,041	0.9034	-	-
Case 3	1,186	0.9437	5.1310	1, 18, 35, 52, 80, 67
Case 4	1,208	0.9548	0.6068	7, 25, 47, 60, 82, 99
Case 5	1,167	0.9182	0.6068	7, 25, 47, 60, 82, 99
Case 6	1,159	0.9034	0.6068	7, 25, 47, 60, 82, 99

The test results from each case study are displayed in Table 3. It is observed that the actual electrical power loss increased in the cases where EV charging stations were installed (Cases 3, 4, 5, and 6) when compared to Case 2 (No EV station). The increases for cases 3, 4, 5, and 6 were approximately 13.9289, 16.0423, 12.1037, and 11.3353%, respectively. The VUF for Cases 3, 4, and 5 also increased by approximately 4.4609, 5.6896, and 1.6383%, respectively, when compared to Case 2. However, there was no change in the VUF for Case 6, as the timing of EV charging was set to a period that the system was not vulnerable. The value of the Electric Vehicle Station Distance (DIS) significantly differed, especially for cases where the EV charging stations were installed at the root node and center point of the group.

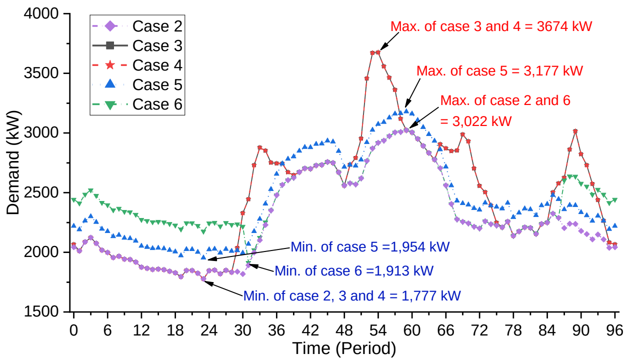

Fig. 21 Comparison of energy demand profiles for Cases 2 to 6 for EVs charging in each zone.

Figure 21 illustrates the electric power demand profile corresponding to each case study. The disparity between the maximum and minimum electric power demands in cases 2, 3, 4, 5, and 6 was 1,244.94, 1,897, 1,897.06, 1,223.48, and 1,109.28 kW, respectively, as indicated by the test results. In contrast, when the difference between the highest and lowest electrical energy demands in cases 3 and 4 was compared to case 2, the corresponding increases were 52.3821 and 52.3768%, respectively. In contrast, cases 5 and 6 exhibited decreases of 1.7240 and 10.8968%, respectively, when compared to case 2. The evaluation of the charging interval for electric vehicles revealed that regulating the electrical energy demand profile could result in an improvement in the aforementioned profiles.

5. Conclusion

This study successfully presented a method for determining the optimum installation point of an EV charging station from a central point based on the distance of the power transmission line. This approach is different from the conventional consideration, which consider installations near the power supply. The center distance of the load group is used as an important target function for the installation of electric vehicle charging stations with complex charging patterns, which vary according to the driver's behaviour. The results showed that the installation of charging stations at the center of the load group (case 4) had a greater effect on loss of electricity and VUF than installing it at the source of the load group (case 3), with increases of 2.1134 and 1.2287%, respectively. The average distance an electric vehicle travels from a potential location to the center of the system is considered essential. However, centralized charging interval control for electric vehicles could reduce the impact during periods of system weaknesses. The results showed that the off-peak charge interval control (Case 6) had the lowest loss of electricity and VUF compared to Case 3, which was 4.7070 and 5.6896%, respectively. In addition, centralized charging interval control for EVs could effectively reduce energy demand during peak power demand range.

In summary, this study proposes installing EV charging station at the center of the load group under center load distance conditions. When applied in conjunction with controlling the timing of electric vehicle charging, it can be an important guideline for planning future improvements to the actual electrical system.

References

[1] H. T. Dinh, J. Yun, D. M. Kim, K. H. Lee, and D. Kim, "A Home Energy Management System With Renewable Energy and Energy Storage Utilizing Main Grid and Electricity Selling," *IEEE Access*, vol. 8, pp. 49436-49450, 2020, doi:10.1109/ACCESS.2020. 2979189.

[2] Y. Chu, Z. Wei, X. Fang, S. Chen, and Y. Zhou, "A Multiagent Federated Reinforcement Learning Approach for Plug-In Electric Vehicle Fleet Charging Coordination in a Residential Community," *IEEE Access*, vol. 10, pp. 98535-98548, 2022, doi:10.1109/ ACCESS. 2022.3206020.

[3] M. Mohammadi-Landi, M. Rastegar, M. Mohammadi, and S. Afrasiabi, "Stochastic Optimal Sizing of Plug-in Electric Vehicle Parking Lots in Reconfigurable Power Distribution Systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 17003-17014, 2022, doi: 10.1109/TITS.2022.3166781.

[4] N. Chitgreeyan, Y. Kongjeen, K. Buayai, and K. Kerdchuen, "Impact of Voltage Unbalance System on Modern Microgrid System under High Penetration of Fast Charging Station," *GMSARN International Journal*, vol. 15, pp. 353-359, 2021.

[5] V. Monteiro, J. A. Afonso, J. C. Ferreira, and J. L. Afonso, "Vehicle electrification: New challenges and opportunities for smart grids," *Energies*, vol. 12, no. 1, p. 118, 2018.

[6] S. A. A. Rizvi, A. Xin, A. Masood, S. Iqbal, M. U. Jan, and H. Rehman, "Electric vehicles and their impacts on integration into power grid: A review," in *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*, 2018, IEEE, pp. 1-6.

[7] M. Ebrahimi, M. Ebrahimi, M. Shafie-khah, and H. Laaksonen, "The Role of EV Parking Lots for Supporting the Distribution System Operation Considering EV Uncertainties," *Transportation Research Procedia,* vol. 70, pp. 263-270, 2023.

[8] F. van Triel and T. E. Lipman, "Modeling the future California electricity grid and renewable energy integration with electric vehicles," *Energies,* vol. 13, no. 20, p. 5277, 2020.

[9] S. Alotaibi, S. Omer, S. Aljarallah, and Y. Su, "Potential implementation of EVs–Features, Challenges and User perspective," in *2021 IEEE Green Energy and Smart Systems Conference (IGESSC)*, 2021, IEEE, pp. 1-10.

[10] W. Li, R. Long, H. Chen, F. Chen, X. Zheng, and M. Yang, "Effect of policy incentives on the uptake of electric vehicles in China," *Sustainability,* vol. 11, no. 12, p. 3323, 2019.

[11] M. Nour, S. M. Said, A. Ali, and C. Farkas, "Smart charging of electric vehicles according to electricity price," in *2019 international conference on innovative trends in computer engineering (ITCE)*, 2019, IEEE, pp. 432-437.

[12] G. Vishnu, D. Kaliyaperumal, R. Jayaprakash, A. Karthick, V. Kumar Chinnaiyan, and A. Ghosh, "Review of Challenges and Opportunities in the Integration of Electric Vehicles to the Grid," *World Electric Vehicle Journal,* vol. 14, no. 9, p. 259, 2023. [Online]. Available: https://www.mdpi.com/2032-6653/14/9/259.

[13] S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, "Review of Electric Vehicle Charging Technologies, Standards, Architectures, and Converter Configurations," *IEEE Access,* vol. 11, pp. 41218-41255, 2023, doi: 10.1109/ACCESS.2023.3267164.

[14] B. Yosrueangsak, C. Summatta, P. Prabpal, N. Thaitae, and S. Sonasang, "Impact of V2G in microgrid systems with PFC," in *20 th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, Nakhon Phanom, Thailand, 2023, pp. 1-4, doi: 10.1109/ECTI-CON58255.2023.10153286.

[15] R. Saadati, M. Jafari-Nokandi, J. Saebi, and S. H. Hosseini, "Optimal location of fast charging stations alongside pricing design from distribution company viewpoint considering renewable energy resource: A modified capacitated flow-capturing location model," *Sustainable Energy, Grids and Networks,* vol. 34, p. 100989, 2023/06/01/ 2023, doi: https:// doi.org/10.1016/j.segan. 2022.100989.

[16] H. Woo, Y. Son, J. Cho, S.-Y. Kim, and S. Choi, "Optimal expansion planning of electric vehicle fast charging stations," *Applied Energy,* vol. 342, p. 121116, 2023/07/15/ 2023, doi: https:// doi.org/ 10.1016/ j.apenergy.2023.121116.

[17] E. A. Rene, W. S. Tounsi Fokui, and P. K. Nembou Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation," *Green Energy and Intelligent Transportation,* vol. 2, no. 3, p. 100094, 2023/06/01/ 2023, doi: https://doi.org/10.1016/j.geits.2023.100094.

[18] V.-H. Bui, A. Hussain, S. Zarrabian, P. M. Kump, and W. Su, "Clustering-based optimal operation of charging stations under high penetration of electric vehicles," *Sustainable Energy, Grids and Networks,* vol. 36, p. 101178, 2023/12/01/ 2023, doi: https:// doi.org/10.1016/j.segan.2023.101178.

[19] M. Nurmuhammed, O. Akdağ, and T. Karadağ, "A novel modified Archimedes optimization algorithm for optimal placement of electric vehicle charging stations in distribution networks," *Alexandria Engineering Journal,* vol. 84, pp. 81-92, 2023/12/01/ 2023, doi: https://doi.org/10.1016/j.aej.2023.10.055.

[20] S. Su, C. Wei, Z. Li, M. Xia, and Q. Chen, "Critical load restoration in coupled power distribution and traffic networks considering spatio-temporal scheduling of electric vehicles," *International Journal of Electrical Power & Energy Systems,* vol. 141, p. 108180, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.ijepes. 2022. 108180.

[21] W. Alabri and D. Jayaweera, "Optimal coordination of unbalanced power distribution systems with integrated photovoltaic systems and semi-fast electric vehicles charging stations," *IET Generation, Transmission & Distribution,* vol. 16, no. 12, pp. 2399-2415, 2022, [Online]. Available: https://mdpi-res.com/d_attachment/life/life-13-02171/article_deploy/life-13-02171.pdf?version=1699242724.

[22] V. Vijayan, A. Mohapatra, S. N. Singh, and C. L. Dewangan, "An Efficient Modular Optimization Scheme for Unbalanced Active Distribution Networks With Uncertain EV and PV Penetrations," *IEEE Transactions on Smart Grid,* vol. 14, no. 5, pp. 3876-3888, 2023, doi: 10.1109/TSG.2023.3234551.

[23] M. R. Kikhavani, A. Hajizadeh, and A. Shahirinia, "Charging coordination and load balancing of plug-in electric vehicles in unbalanced low-voltage distribution systems," *IET Generation, Transmission & Distribution,* vol. 14, no. 3, pp. 389-399, 2020, doi: https://doi.org/10.1049/iet-gtd.2019.0397.

[24] M. R. Feizi, M. E. Khodayar, and J. Li, "Data-driven distributionally robust unbalanced operation of distribution networks with high penetration of photovoltaic generation and electric vehicles," *Electric Power Systems Research,* vol. 210, p. 108001, 2022/09/01/ 2022, doi: https:// doi.org/ 10.1016/ j.epsr. 2022.108001.

[25] N. C. Yang and Y. W. Hsu, "OpenDSS-Based Harmonic Power Flow Analysis for Distribution Systems With Passive Power Filters," *IEEE Access,* vol. 11, pp. 69190-69203, 2023, doi: 10.1109/ ACCESS. 2023.3292286.

[26] V. C. Cunha, T. Kim, P. Siratarnsophon, N. Barry, S. Santoso, and W. Freitas, "Quasi-Static Time-Series Power Flow Solution for Islanded and Unbalanced Three-Phase Microgrids," *IEEE Open Access Journal of Power and Energy,* vol. 8, pp. 97-106, 2021, doi: 10.1109/OAJPE.2021.3062312.

[27] R. C. Dugan and D. Montenegro, "Reference Guide The Open Distribution System Simulator (OpenDSS)," *Electric Power Research Institute, Inc. ,* Nov. 2022.

[28] M. Purlu and B. E. Turkay, "Optimal Allocation of Renewable Distributed Generations Using Heuristic Methods to Minimize Annual Energy Losses and Voltage Deviation Index," *IEEE Access,* vol. 10, pp. 21455-21474, 2022, doi: 10.1109/ACCESS. 2022. 3153042.

[29] A. Kharrazi and V. Sreeram, "Mitigation of Voltage Unbalance in Distribution Feeders Using Phase Switching Devices: A Decentralized Control Approach Based on Local Measurements," *IEEE Transactions on Power Delivery,* vol. 37, no. 4, pp. 2875-2885, 2022, doi: 10.1109/TPWRD.2021.3118917.

[30] S. Manjang and Y. Asmi RAHMAN, "Distributed photovoltaic integration as complementary energy: consideration of solutions for power loss and load demand growth problems," *Przegląd Elektrotechniczny,* vol. 1, no. 9, pp. 56-61, 2020, doi: 10.15199/ 48.2020.09.12.

[31] C. Zedak, A. Belfqih, A. Lekbich, J. Boukherouaa, and F. El Mariami, "Optimal planning and management of photovoltaic sources and battery storage systems in the electricity distribution networks," *Przegląd Elektrotechniczny,* vol. 1, no. 8, pp. 95-101, 2020, doi: 10.15199/48.2020.08.19.

[32] N. Wojciech and F. Sylwester, "Optymalizacja modernizacji terenowych linii elektroenergetycznych SN z zastosowaniem algorytmów ewolucyjnych," *Przeglad Elektrotechniczny,* vol. 1, no. 11, pp. 26-33, 2023, doi: 10.15199/48.2023.11.05.

[33] Z. Ren, X. Qu, M. Wang, and C. Zou, "Multi-Objective Optimization for DC Microgrid Using Combination of NSGA-II Algorithm and Linear Search Method," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems,* vol. 13, no. 3, pp. 789-796, 2023, doi: 10.1109/JETCAS.2023.3284061.

[34] J. Li, L. Shi, and H. Fu, "Multi-Objective Short-Term Optimal Dispatching of Cascade Hydro– Wind– Solar– Thermal Hybrid Generation System with Pumped Storage Hydropower," *Energies,* vol. 17, no. 1, p. 98, 2024, [Online]. Available: https://www.mdpi.com/1996-1073/17/1/98.

[35] H. Wei, J. Liang, C. Li, and Y. Zhang, "Real-time Locally Optimal Schedule for Electric Vehicle Load via Diversity-maximization NSGA-II," *Journal of Modern Power Systems and Clean Energy,* vol. 9, no. 4, pp. 940-950, 2021, doi: 10.35833/ MPCE. 2020. 000093.

[36] S. L. Wynn, W. Pinthurat, and B. Marungsri, "Multi-Objective Optimization for Peak Shaving with Demand Response under Renewable Generation Uncertainty," *Energies,* vol. 15, no. 23, 2022, doi: 10.3390/en15238989.

[37] R. Lin, Z. He, H. Zou, and B. Wu, "Load Data Analysis Based on Timestamp-Based Self-Adaptive Evolutionary Clustering," *IEEE Transactions on Industrial Informatics,* vol. 19, no. 12, pp. 11508-11517, 2023, doi: 10.1109/TII.2023.3247010.

[38] L. Gaitan, J. Gómez, and E. Rivas, "Quasi-Dynamic Analysis of a Local Distribution System with Distributed Generation. Study Case: The IEEE 13 Node System," *TecnoLógicas,* vol. 22, pp. 195-212, 09/20 2019, doi: 10.22430/22565337.1489.

[39] T. U. Solanke, V. K. Ramachandaramurthy, J. Y. Yong, J. Pasupuleti, P. Kasinathan, and A. Rajagopalan, "A review of strategic charging–discharging control of grid-connected electric vehicles," *Journal of Energy Storage,* vol. 28, p. 101193, 2020/04/01/ 2020, doi: https://doi.org/10.1016/j.est.2020.101193.